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Price-pressure implied volatility spread (PIVS): A novel predictor for stock market volatility

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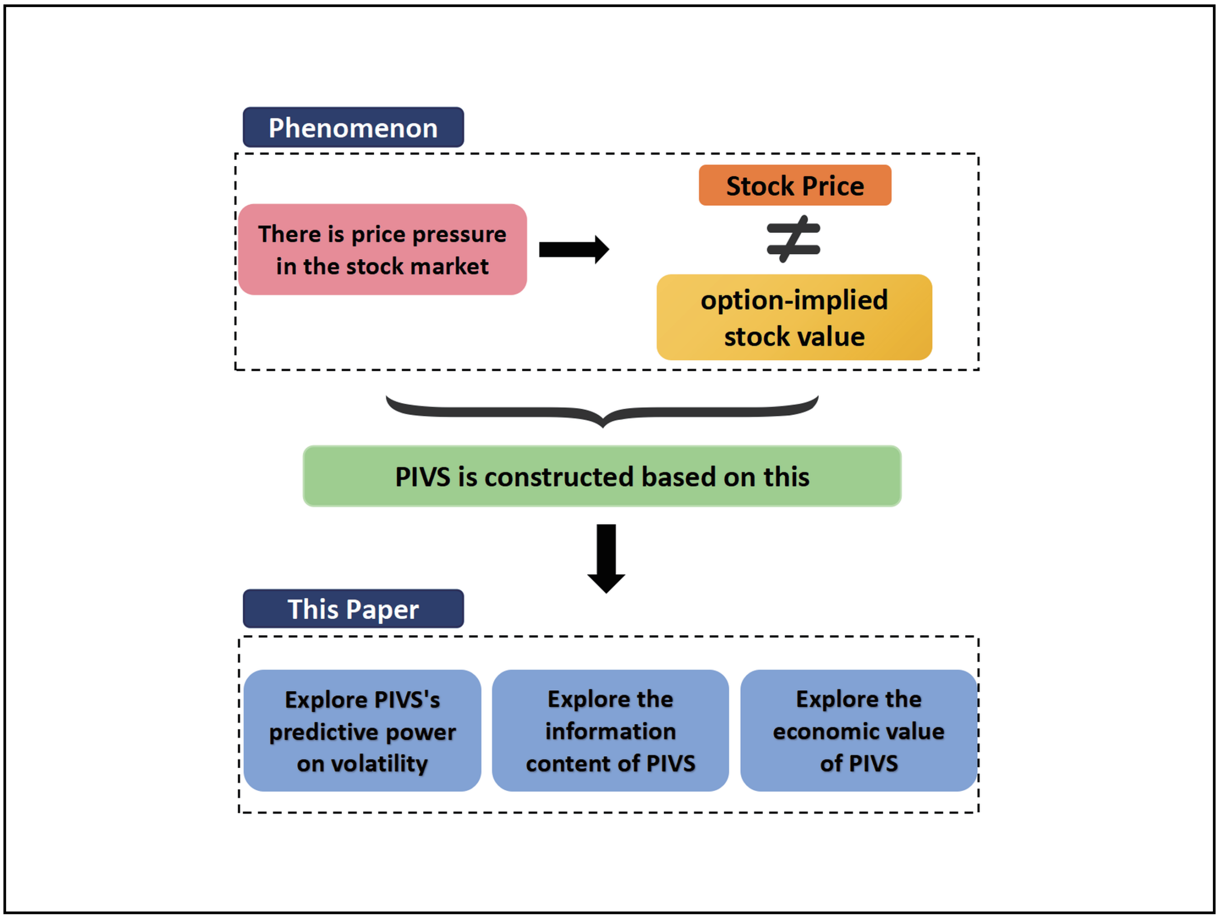
Graphical abstract



We construct a price-pressure implied volatility spread (PIVS) factor and investigates its predictive power for stock market volatility.

Public summary

- This paper introduces a new factor, the Price-Pressure Implied Volatility Spread (PIVS), which is constructed on the basis of the the relationship between the stock and options markets.
- PIVS exhibits significant and robust predictive power for market volatility.
- Beyond statistical performance, we also demonstrate that PIVS holds significant economic value.

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Abstract: This paper constructs a price–pressure implied volatility spread (PIVS) factor on the basis of the the different information reflected in the stock and options markets and investigates its predictive power for stock market volatility. We find that PIVS significantly and robustly predicts short-term volatility. Furthermore, the factor provides incremental predictive insights that complement existing volatility predictors, suggesting its potential utility as an additional instrument for volatility forecasting.

Keywords: implied volatility spread; price pressure; volatility forecasting; options

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2020 Mathematics Subject Classification: 91G15

1 Introduction

A growing body of research has demonstrated the value of option-implied information in forecasting stock returns and volatility[1–9]. Several studies have shown that this predictive ability is driven primarily by price pressures in the stock market, with the options market providing a more accurate reflection of stock prices[5,10–12]. Notably, Goncalves-Pinto et al.[11] highlights the relationship between implied volatility spreads (IVS) and stock price movements, noting that this relationship is associated with price pressures in the market. This insight forms the foundation for constructing a price-pressure implied volatility spread (PIVS) factor. Our study explores how this factor can be used to predict market volatility.

The implied volatility spread (IVS) refers to the difference in implied volatility between call and put options on the same underlying asset. An IVS value can be calculated for each strike price. We interpret IVS values that move contrary to stock price changes as signals of price pressure. By averaging these values, we create the price-pressure implied volatility spread (PIVS) factor. To ensure a comprehensive analysis, we also: (i) average IVS values that align with the stock price movement to construct a non-price-pressure IVS factor (NIVS), and (ii) average IVS values across all strike prices to develop a total IVS factor (TIVS). We first explore the predictive power of these IVS factors in forecasting volatility. In addition, we assess the incremental forecasting ability of these IVS factors relative to other established volatility predictors. Finally, we evaluate the economic value of these factors.

Our results reveal three key findings. First, we demonstrate that PIVS significantly and robustly predicts short-term volatility. Second, we show that PIVS contains valuable information not captured by other volatility predictors, thus enhancing their forecasting accuracy. Third, we assess its economic impact and reveal that the PIVS can substantially improve portfolio returns.

Our study makes three main contributions. First, unlike previous studies that use implied higher-order moments (e.g., VIX, SKEW) for prediction[4,13], we construct a novel factor, PIVS, by integrating the difference in implied volatility between call and put options with the relationship between the stock and options markets. Second, we find that the PIVS has strong and robust predictive power for market volatility. Finally, unlike studies that focus solely on the statistical performance of factors[14–16], we demonstrate not only that the PIVS is a reliable volatility predictor but also that it has significant economic value.

The paper is structured as follows: Section 2 details the construction of different IVS factors. Section 3 outlines the evaluation framework. Section 4 describes the data sources. Section 5 presents the empirical findings. Section 6 conducts robustness checks. Section 7 analyzes the economic value of our volatility forecasts. Section 8 concludes the paper. The Appendix presents supplementary robustness analyses and a theoretical rationale for the predictive power of IVS factors.

2 IVS factors and other predictors

2.1 The IVS factors

On day t, the IVS for an option with strike price k is defined as:

$$IVS_{t,k} = IV_{t,k}^{Call} - IV_{t,k}^{Put}, \quad k \in \mathbb{N}_t = \{k_{1,t}, k_{2,t}, \cdots, k_{n_t,t}\},$$

where $IVS_{t,k}$ denotes the implied volatility spread for the option with strike price k on day t, and $IV_{t,k}^{Call}$ ($IV_{t,k}^{Put}$) represents

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JUSTC, **2025**, 55(X):

the implied volatility of the call (put) option with strike price k on day t. The set $\mathbb{N}_t$ contains all available strike prices on day t, where $k_{i,t}$ refers to the i-th strike price and n_t is the total number of strike prices on that day.

Following the price pressure mechanism proposed by Goncalves-Pinto et al.[11], price pressure arises when option market signals contradict intraday stock price movements. We compute the price-pressure implied volatility spread (PIVS) by averaging IVS values that oppose the day's price change:

$$\Delta S_t = S_{\text{close},t} - S_{\text{open},t},$$
$$PIVS_t = \frac{1}{|\mathbb{N}_t^P|}\sum_{k\in\mathbb{N}_t^P} IVS_{t,k},$$
$$\mathbb{N}_t^P = \{k \in \mathbb{N}_t : \text{sgn}(\Delta S_t) \neq \text{sgn}(IVS_{t,k})\},$$

where ΔS_t is the daily stock price change, and $S_{\text{close},t}$ and $S_{\text{open},t}$ denote the closing and opening stock prices on day t, respectively. $PIVS_t$ represents the PIVS on day t, and the set $\mathbb{N}_t^P$ identifies strike prices with the IVS opposing the daily price movement.

For completeness, we define the nonprice-pressure implied volatility spread (NIVS) by averaging IVS values aligned with the daily price movement:

$$NIVS_t = \frac{1}{|\mathbb{N}_t^N|}\sum_{k\in\mathbb{N}_t^N} IVS_{t,k},$$
$$\mathbb{N}_t^N = \{k \in \mathbb{N}_t : \text{sgn}(\Delta S_t) = \text{sgn}(IVS_{t,k})\},$$

where $NIVS_t$ represents the NIVS on day t, the set $\mathbb{N}_t^N$ identifies strike prices with IVS aligns with the daily price movement.

Finally, we compute the total implied volatility spread (TIVS) by averaging IVS across all strike prices:

$$TIVS_t = \frac{1}{n_t}\sum_{k\in\mathbb{N}_t} IVS_{t,k},$$

where $TIVS_t$ represents the total implied volatility spread on day t.

2.2 Other Predictors

We compare IVS factors against established volatility predictors: trading volume (VOL)[17], risk-neutral skewness (SKEW)[4], investor sentiment (SEN)[18], and economic policy uncertainty (EPU)[19]. Daily S&P 500 volume and news sentiment indices[20] proxy market activity and investor sentiment.

2.3 Realized volatility

Following Andersen and Bollerslev[21], we compute daily realized volatility (RV) by summing the squared intraday returns from high-frequency trading data. For a given business day t, the RV is calculated as follows:

$$RV_t = \sum_{j=1}^{M} r_{t,j}^2,$$

where RV_t denotes the RV for day t; $r_{t,j}$ represents the j-th intraday return on day t, $M = 1/\Delta$, where Δ is the sampling interval and M represents the number of intervals within a day. By utilizing the daily RV, the multiperiod RVs are defined as:

$$RV_{t,t+h} = (RV_t + RV_{t+1} + \cdots + RV_{t+h-1})/h,$$

where $RV_{t,t+h}$ indicates the average RV from day t to day $t+h$ and where h denotes the time horizon; daily, weekly, and monthly variances correspond to $h = 1$, 5, and 22, respectively.

3 Evaluation method

We assess forecasting performance via the out-of-sample R^2 introduced by Campbell and Thompson[22]. This test measures the percentage reduction in the mean squared predictive error (MSPE) of a model in comparison to a benchmark, offering a clear metric for performance evaluation. The out-of-sample R^2 (R^2_{os}) is calculated as:

$$R^2_{\text{os}} = 1 - \frac{MSPE_{model}}{MSPE_{bench}},$$

where $MSPE_i = \frac{1}{L}\sum_{t=1}^{L}(RV_t - \widehat{RV}_{t,i})$ for $i =$ *model* or *bench* and where L represents the length of the out-of-sample period. A positive R^2_{os} value indicates that our model achieves a lower MSPE than the benchmark does, indicating superior forecasting accuracy. To assess whether this improvement is statistically significant, we also employ the Clark–West test[23], which is specifically designed to test the predictive superiority of nested models in an out-of-sample setting.

4 Data

In this study, we quantify market volatility via the daily realized volatility (RV) of the S&P 500 (SPX), which is derived from high-frequency trading data from Pi-Trading. We construct the implied volatility spread via S&P 500 option data from the OptionMetrics database. Additional predictors, including economic policy uncertainty (EPU)[19], risk-neutral skewness (SKEW)[4], and the daily sentiment index (SEN)[18], are obtained from the Federal Reserve Economic Data (FRED) and the Federal Reserve Bank of San Francisco.

Table 1 provides descriptive statistics for the IVS factors and other predictors. The autocorrelations for PIVS, NIVS, and TIVS are low, with first-order autocorrelations of approximately 0.1. These findings suggest that these variables are not significantly affected by persistent predictive factors[24]. Additionally, the correlations between the IVS factors and other predictors are all less than 0.1, indicating that the IVS factors offer distinct information.

Fig. 1 shows the time series of PIVS, NIVS, and TIVS from 2000 to 2019. All three IVS types experienced sharp fluctuations during the financial crisis.

5 Empirical results

In this subsection, we utilize a rolling estimation window to generate out-of-sample volatility forecasts. Specifically, the entire sample is split into two parts: The first 1260 (252 days per year over five years) observations form the in-sample estimation section, whereas the subsequent 3750 observations are allocated for out-of-sample forecasting. As new data become available, we advance the estimation window by one

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Table 1. Summary statistics of the key variables.

	Mean	Std	Autocorrelation at lag			Pearson correlation						
			1.000	3.000	6.000	PIVS	NIVS	TIVS	EPU	SKEW	VOL	SEN
PIVS	−0.001	0.025	0.060	0.115	0.015	1.000						
NIVS	0.000	0.022	0.089	0.031	0.058	−0.024	1.000					
TIVS	−0.001	0.033	0.181	0.114	0.086	0.741	0.642	1.000				
EPU	98.814	66.096	0.607	0.502	0.450	−0.041	−0.038	−0.057	1.000			
SKEW	121.420	8.164	0.930	0.876	0.815	−0.012	0.052	0.025	−0.140	1.000		
VPL	3.1E+09	1.7E+09	0.933	0.890	0.868	−0.040	−0.060	−0.074	0.264	−0.178	1.000	
SEN	0.024	0.190	0.997	0.988	0.973	0.053	0.051	0.076	−0.475	0.167	−0.477	1.000

This table presents descriptive statistics for the IVS factors and other predictors as well as their correlations. Detailed descriptions of the variables and their constructions are provided in Section 2.

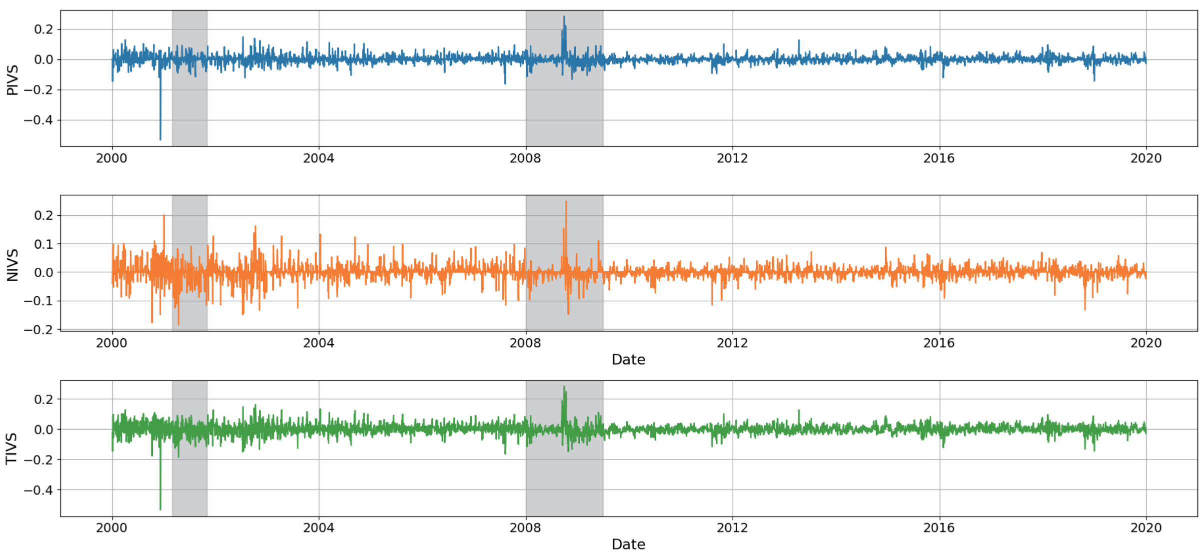

Fig. 1. Time series of the IVS factors. This figure depicts the time series of the PIVS, NIVS, and TIVS. The sample period is from January 2000 to December 2019. The gray areas indicate the National Bureau of Economic Research recession periods.

step to produce updated out-of-sample volatility forecasts.

5.1 Out-of-sample prediction results

We benchmark our analysis using the heterogeneous autoregressive model (HAR) for realized volatility, as introduced by Corsi[25], and compare the forecast performance of each predictor Z with that of the HAR model.

Benchmark 1:

$$RV_{t,t+h} = HAR + \varepsilon_{t,t+h}.$$

Model 1:

$$RV_{t,t+h} = HAR + \gamma Z_{t-1} + \varepsilon_{t,t+h},$$

where HAR abbreviates $\beta_0 + \beta_D RV_{t-1} + \beta_W RV_{t-5,t} + \beta_M RV_{t-22,t}$; Z_{t-1} denotes the variables for day $t-1$; γ measures the influence of Z_{t-1} on volatility forecasting; and ε_{t+h} is the error term.

Table 2 presents the out-of-sample R^2 results under Benchmark 1, along with their statistical significance based on the Clark–West test. For short- and medium-term volatility forecasts, HAR-NIVS and HAR-TIVS produce negative or insignificant R^2 values, whereas HAR-PIVS consistently delivers a statistically significant and positive R^2. For instance, in the one-day forecast, HAR-PIVS achieves a value of 1.354%, whereas −0.005% and −0.137% for HAR-NIVS and HAR-TIVS, respectively. A similar pattern holds for the five-day forecast. In contrast, models based on IVS factors yield statistically insignificant results for long-term predictions. The above results show that NIVS and TIVS have limited predictive power for volatility, whereas PIVS captures more relevant signals for short-term volatility movements.

Following Welch and Goyal[26], Fig. 2 displays the cumulative differences in squared forecast errors between the benchmark (HAR) and various predictors, including PIVS, NIVS, and TIVS, at the one-day forecast horizon. A larger (more positive) cumulative difference indicates better forecast performance. Consistent with the results in Table 2, Fig. 2 shows that PIVS outperforms the other predictors, particularly during recessions, further confirming its relevance for forecast-

CSTR: 32290.14.JUSTC-2025-0031
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JUSTC, **2025**, 55(X):

Table 2. Out-of-sample performance under the out-of-sample R^2 test (Benchmark 1).

	1-day horizon			5-day horizon			22-day horizon		
	R^2_{os} (%)	MSPE-adj	p-value	R^2_{os} (%)	MSPE-adj	p-value	R^2_{os} (%)	MSPE-adj	p-value
HAR	—	—	—	—	—	—	—	—	—
HAR-PIVS	**1.354**	**0.711**	**0.000**	**0.673**	**0.615**	**0.010**	0.016	−0.032	0.232
HAR-NIVS	−0.005	0.070	0.109	−0.288	−0.074	0.142	−0.230	0.246	0.870
HAR-TIVS	−0.137	0.134	0.292	0.017	0.277	0.274	−0.119	0.272	0.431
HAR-EPU	−0.023	0.116	0.161	0.042	0.387	0.073	0.083	0.461	0.154
HAR-SKEW	−0.063	0.103	0.325	−0.113	0.198	0.344	−0.723	0.444	0.160
HAR-VOL	−0.528	0.041	0.719	−0.260	0.334	0.090	0.159	2.242	0.000
HAR-SEN	−0.351	0.065	0.561	0.423	1.013	0.007	**3.846**	**6.681**	**0.000**

This table reports the out-of-sample performance of different models under the out-of-sample R^2 test on Benchmark 1. The statistical significance of R^2_{os} is determined via the p-value from the MSFE-adjusted statistic, referred to as MSFE-adj in the table, following the method described in Clark and West[23]. The out-of-sample R^2 values exceeding 0.5% and statistically significant at the 1% level are highlighted in bold.

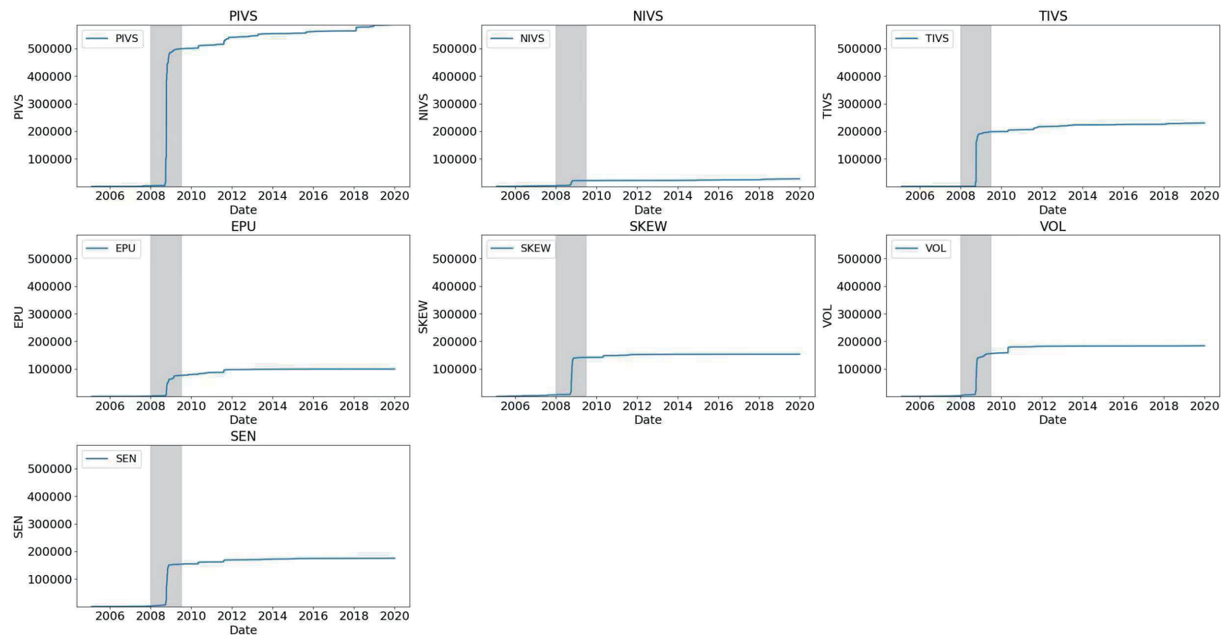

Fig. 2. Out-of-sample performance on the basis of cumulative squared forecast errors. The forecast horizon is one day ahead. Each line represents the cumulative difference in squared forecast errors between Benchmark 1 and the forecasts from other models via the corresponding predictor. The gray vertical bars mark the recession periods identified by the National Bureau of Economic Research. The evaluation period spans from February 2005 to December 2019.

ing short-term volatility.

5.2 The information increment of different IVS factors

To assess the incremental forecasting power of IVS factors, we compare a bivariate predictive regression model that includes both IVS factors and an alternative predictor Z with a univariate regression model using only Z (Benchmark 2).

Benchmark 2:

$$RV_{t,t+h} = HAR + \gamma Z_{t-1} + \varepsilon_{t,t+h}.$$

Model2:

$$RV_{t,t+h} = HAR + bX_{t-1} + cZ_{t-1} + \varepsilon_{t,t+h},$$

where X_{t-1} represents $PIVS_{t-1}$, $NIVS_{t-1}$ or $TIVS_{t-1}$, and Z_{t-1} represents other volatility predictors.

In addition, to further examine the forecasting power of the IVS factors, we include all the predictors except for the IVS factors in the HAR model as Benchmark 3, which we refer to as HAR-KS. We then incorporate different IVS factors into HAR-KS to compare their predictive performance.

Benchmark 3:

$$RV_{t,t+h} = HAR + \sum_{i=1}^{n} \gamma Z_{i,t-1} + \varepsilon_{t,t+h}.$$

Model 3:

$$RV_{t,t+h} = HAR + \sum_{i=1}^{n} \gamma Z_{i,t-1} + cX_{t-1} + \varepsilon_{t,t+h},$$

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JUSTC, **2025**, 55(X):

where X_{t-1} represents $PIVS_{t-1}$, $NIVS_{t-1}$, or $TIVS_{t-1}$, and $Z_{i,t-1}$ represents other volatility predictors. The variable n represents the total number of other volatility predictors. In Benchmarks 2 and 3, we include five volatility predictors in total: EPU, SKEW, VOL, SEN, and VIX (the implied volatility index).

Table 3 presents the out-of-sample R^2 results based on Benchmark 2 and Benchmark 3, along with their statistical significance assessed via the Clark–West test. For short- and medium-term volatility forecasts, incorporating PIVS significantly reduces out-of-sample prediction errors compared with models that rely on existing volatility predictors. This demonstrates that PIVS provides valuable information that enhances model performance. In contrast, NIVS and TIVS do not significantly improve prediction accuracy, suggesting that they do not offer meaningful insights for forecasting volatility. Furthermore, for long-term volatility prediction, the out-of-sample R^2 values for almost all the predictors are not significant, indicating that they provide limited information for these time horizons.

6 Robustness checks

6.1 Different forecasting windows

Rossi and Inoue[27] highlights that prediction results can be sensitive to the sample length. To address this, we conduct a robustness check by using different in-sample window lengths of four and six years to estimate the model, reserving the remaining data for prediction. The results of these robustness tests are shown in Table 4. Consistent with our previous findings, PIVS, the IVS factor derived from stock price pressure, provides more relevant information for predicting volatility. Further robustness test results can be found in the Appendix.

7 Economic value analysis

For market investors, the economic significance of volatility forecasts outweighs their statistical performance. In this section, we evaluate the economic benefits of different volatility forecast models by considering a mean-variance utility in-

Table 3. Out-of-sample performance under the out-of-sample R^2 test (Benchmarks 2 & 3).

	1-day horizon			5-day horizon			22-day horizon		
	$R^2_{\rm os}$ (%)	MSPE-adj	p-value	$R^2_{\rm os}$ (%)	MSPE-adj	p-value	$R^2_{\rm os}$ (%)	MSPE-adj	p-value
HAR-EPU	—	—	—	—	—	—	—	—	—
HAR-EPU-PIVS	**1.415**	**0.732**	**0.000**	**0.746**	**0.651**	**0.007**	0.042	0.290	0.216
HAR-EPU-NIVS	−2.127	−0.085	0.738	−0.709	0.128	0.702	0.197	0.307	0.100
HAR-EPU-TIVS	−0.115	0.143	0.276	0.087	0.311	0.201	−0.071	0.270	0.358
HAR-SKEW	—	—	—	—	—	—	—	—	—
HAR-SKEW-PIVS	**1.319**	**0.693**	**0.001**	**0.650**	**0.594**	**0.013**	0.020	0.243	0.260
HAR-SKEW-NIVS	−2.076	−0.086	0.742	−0.748	0.099	0.774	0.214	0.297	0.122
HAR-SKEW-TIVS	−0.097	0.141	0.264	0.059	0.292	0.257	−0.052	0.278	0.381
HAR-VOL	—	—	—	—	—	—	—	—	—
HAR-VOL-PIVS	**1.563**	**0.797**	**0.000**	**0.880**	**0.727**	**0.004**	0.271	0.463	0.093
HAR-VOL-NIVS	−2.325	−0.086	0.783	−0.812	0.139	0.717	−0.015	0.261	0.253
HAR-VOL-TIVS	−0.022	0.175	0.130	0.144	0.343	0.181	0.118	0.418	0.216
HAR-SEN	—	—	—	—	—	—	—	—	—
HAR-SEN-PIVS	**1.499**	**0.748**	**0.000**	**0.820**	**0.675**	**0.006**	0.141	0.346	0.098
HAR-SEN-NIVS	−2.086	−0.076	0.781	−0.796	0.108	0.751	−0.157	0.150	0.369
HAR-SEN-TIVS	−0.043	0.157	0.206	0.182	0.343	0.165	0.098	0.365	0.174
HAR-VIX	—	—	—	—	—	—	—	—	—
HAR-VIX-PIVS	**0.933**	**0.461**	**0.001**	0.494	0.485	0.018	−0.006	0.258	0.227
HAR-VIX-NIVS	−0.243	0.193	0.273	−0.099	0.271	0.361	0.175	0.297	0.109
HAR-VIX-TIVS	−0.021	0.171	0.179	0.081	0.301	0.214	−0.063	0.285	0.362
HAR-KS	—	—	—	—	—	—	—	—	—
HAR-KS-PIVS	**0.822**	**0.436**	**0.003**	**0.685**	**0.581**	**0.008**	0.394	0.492	0.029
HAR-KS-NIVS	−0.271	0.200	0.324	−0.215	0.281	0.345	−0.104	0.214	0.215
HAR-KS-TIVS	0.033	0.193	0.152	0.226	0.367	0.125	0.189	0.380	0.131

This table reports the out-of-sample performance of different models under the out-of-sample R^2 test on Benchmarks 2 & 3. The statistical significance of $R^2_{\rm os}$ is determined via the p-value from the MSFE-adjusted statistic, referred to as MSFE-adj in the table, following the method described in Clark and West[23]. The out-of-sample R^2 values exceeding 0.5% and statistically significant at the 5% level are highlighted in bold.

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Table 4. Out-of-sample performance when different forecasting windows are used.

	1-day horizon			5-day horizon			22-day horizon		
	R^2_{os} (%)	MSPE-adj	p-value	R^2_{os} (%)	MSPE-adj	p-value	R^2_{os} (%)	MSPE-adj	p-value
Length of in-sample window = 252×4 days									
HAR	—	—	—	—	—	—	—	—	—
HAR-PIVS	**1.356**	**0.720**	**0.002**	**0.943**	**0.713**	**0.008**	0.144	0.368	0.162
HAR-NIVS	−0.037	0.077	0.053	−0.324	−0.068	0.383	−0.275	−0.028	0.904
HAR-TIVS	−0.111	0.154	0.328	0.241	0.382	0.215	0.008	0.364	0.318
HAR-EPU	−0.036	0.109	0.173	0.186	0.464	0.035	0.005	0.436	0.192
HAR-SKEW	0.016	0.127	0.178	0.156	0.303	0.147	0.236	1.130	0.003
HAR-VOL	−0.715	−0.006	0.961	−0.033	0.354	0.053	0.425	0.000	2.088
HAR-SEN	−0.367	0.052	0.622	**0.597**	**1.009**	**0.006**	**3.773**	**6.110**	**0.000**
Length of in-sample window = 252×6 days									
HAR	—	—	—	—	—	—	—	—	—
HAR-PIVS	**1.374**	**0.714**	**0.000**	**0.610**	**0.558**	**0.005**	−0.062	0.193	0.307
HAR-NIVS	0.145	0.105	0.028	−0.165	−0.041	0.149	−0.187	−0.054	0.547
HAR-TIVS	−0.023	0.138	0.168	0.058	0.235	0.163	−0.193	0.114	0.567
HAR-EPU	−0.011	0.116	0.163	0.017	0.336	0.093	0.005	0.326	0.198
HAR-SKEW	−0.205	0.064	0.580	−0.251	0.125	0.572	−0.517	0.440	0.123
HAR-VOL	−0.005	0.140	0.162	0.041	0.421	0.009	−0.196	1.909	0.000
HAR-SEN	−0.310	0.078	0.524	0.208	0.990	0.009	**2.563**	**6.420**	**0.000**

This table shows the out-of-sample R^2 test for two alternative forecasting windows. The statistical significance of R^2_{os} is determined via the p-value from the MSFE-adjusted statistic, referred to as MSFE-adj in the table, following the method described in Clark and West[23]. The out-of-sample R^2 values exceeding 0.5% and statistically significant at the 1% level are highlighted in bold.

vestor who allocates assets between the SPX and a risk-free asset. We base the utility function on the approach of Rapach et al.[28] and Ye et al.[29], which is expressed as follows:

$$U(r_i) = E_i(\omega_i\hat{r}_i + r_{f,i}) - \frac{1}{2}\gamma Var_i(\omega_i\hat{r}_i + r_{f,i}),$$

where ω_i is the weight of the SPX in the portfolio on day i, $\hat{r}_i$ is the excess return of the SPX ($\hat{r}_i = r_i - r_{f,i}$), r_i is the SPX return, $r_{f,i}$ is the risk-free interest rate, and γ is the risk aversion coefficient. We use the 3-month U.S. Treasury yield as the risk-free rate.

Maximizing the utility function $U(r_i)$ with respect to ω_i yields the ex-ante optimal weight of the SPX on day $i+1$:

$$\hat{\omega}_i = \frac{1}{\gamma}\left(\frac{\hat{r}_{i+1}}{R\hat{V}_{i+1}}\right),$$

where $\hat{r}_{i+1}$ is the average excess returns of the past 252 days, and $R\hat{V}_{i+1}$ is the predicted realized volatility. Since the excess returns are the same across models, the portfolio's optimal weight depends on the realized volatility predicted by each model at different levels of risk aversion. The portfolio return on day $i+1$ is as follows:

$$R_{p,i+1} = \hat{w}_i\hat{r}_{i+1} + r_{f,i+1}.$$

To evaluate portfolio performance, we use two common metrics: the Sharpe ratio (SR) and the certainty-equivalent return (CER).

The Sharpe ratio is as follows:

$$SR_p = \frac{\bar{\mu}_p}{\bar{\sigma}_p}.$$

The CER is:

$$CER_p = \hat{\mu}_p - \frac{\gamma}{2}\hat{\sigma}^2_p,$$

where $\hat{\mu}_p$ and $\hat{\sigma}^2_p$ are the mean and variance of the portfolio's excess returns, respectively. We set $\gamma = 1, 3$, or 5 to represent different risk aversion levels.

Fig. 3 shows the annualized return, annualized CER gain, and Sharpe ratio (SR) of portfolios formed via volatility forecasts for three risk aversion levels. The CER gain represents the difference between the CER for an investor via our proposed models and one using the variance of past stock returns over a 1-year rolling window. The results indicate that HAR-PIVS outperforms the other models in terms of return, CER, and SR across all risk aversion levels. These findings suggest that the future volatility information in the PIVS enhances the economic value of the portfolio when added to the benchmark model, which is consistent with the out-of-sample results.

8 Conclusions

This study constructs the PIVS factor on the basis of the the relationship between the stock and options markets and examines its predictive power for market volatility. Our results re-

CSTR: 32290.14.JUSTC-2025-0031
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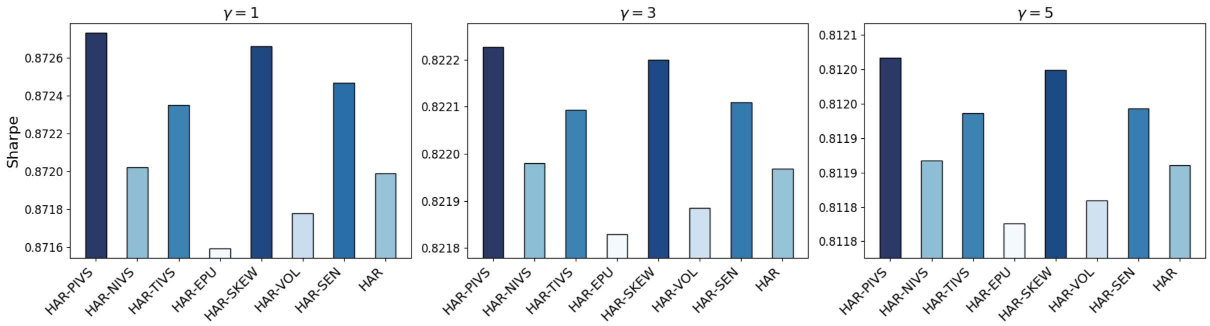
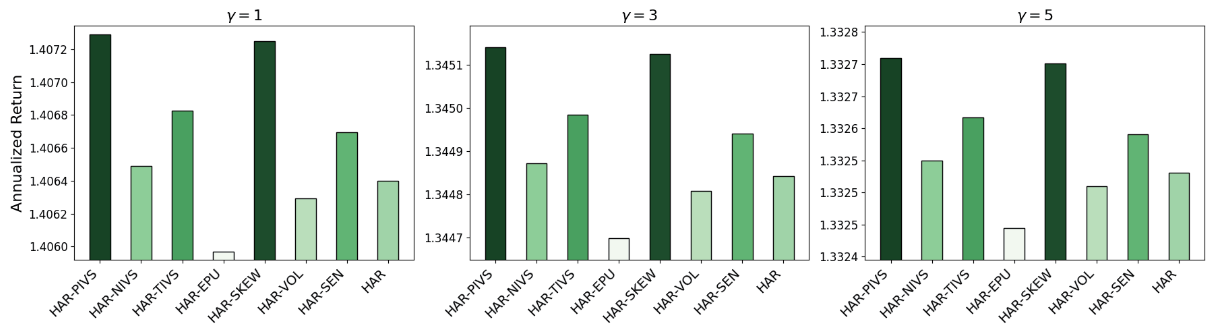
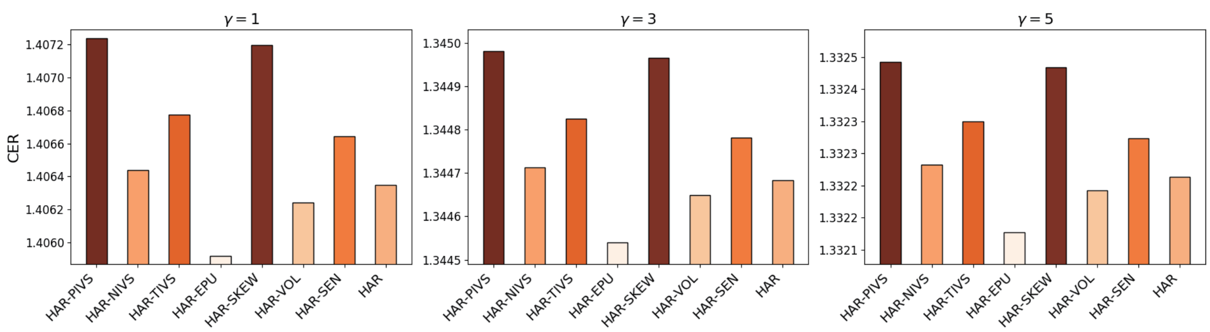
JUSTC, **2025**, 55(X):



(a) Sharpe ratio across different gammas



(b) Annualized return (R%) as percentage across different gammas



(c) Certainty-equivalent return (CER%) gain in percentage across different gammas

Fig. 3. Portfolio Performance Based on Volatility Forecasts from Different Models. This figure presents the portfolio performance of different models, showing the annualized return (R) in percentage, the annualized certainty-equivalent return (CER) gain in percentage, and the Sharpe ratio (SR) for portfolios using a mean-variance utility function. This function reflects an investor's allocation between the SPX and a risk-free asset, with risk aversion captured by γ. The CER gain represents the difference between the CER for an investor using our proposed volatility forecasts and the CER using the variance of past stock returns over a 1-year rolling window.

veal three key findings. First, PIVS is a significant and robust volatility predictor. Second, PIVS contains valuable information not captured by other volatility predictors, thereby increasing its forecasting accuracy. Third, in addition to its strong statistical performance, PIVS also demonstrates significant economic value.

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Conflict of interest

The authors declare that they have no conflict of interest.

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CSTR: 32290.14.JUSTC-2025-0031
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Appendix

We provide additional robustness test results to ensure the reliability of our conclusions.

A.1 Log-transformation of RV estimates

To further validate our conclusions, we apply the logarithmic transformation to RV, defining $LV_t = \log(RV_t)$ and $LV_{t,t+h} = \log(RV_{t,t+h})$, as suggested by Paye[14]. This transformation normalizes the distribution, improving the accuracy of volatility modeling and prediction. Our Benchmark 1 and Model 1 are now updated as follows.

Benchmark 3:

$$LV_{t,t+h} = HARL + \varepsilon_{t,t+h}.$$

Model 3:

$$LV_{t,t+h} = HARL + \gamma Z_{t-1} + \varepsilon_{t,t+h},$$

where $HARL$ represents $\beta_0 + \beta_D LV_{t-1} + \beta_W LV_{t-5,t} + \beta_M LV_{t-22,t}$; Z_{t-1} denotes the predictor for day $t-1$, and γ measures the influence of Z_{t-1} on volatility forecasting.

Table A1 presents the out-of-sample R^2 test results based on Benchmark 3 (using the HARL model's results as the predicted volatility). The conclusions from this test are consistent with our earlier findings: the PIVS, the IVS factor derived from stock price pressure, provides more relevant information for predicting volatility.

A.2 Different forecasting sub-periods

Finally, we replicated our experiments via different forecasting periods. Specifically, we divided the full forecasting period (from January 2, 2000, to December 31, 2019) into two equal subperiods: January 2, 2000, to December 31, 2009 and January 3, 2010,

CSTR: 32290.14.JUSTC-2025-0031
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JUSTC, **2025**, 55(X):

Table A1. Out-of-sample R^2 results based on the logarithmic transformation of Benchmark 1.

	1-day horizon			5-day horizon			22-day horizon		
	R^2_{os} (%)	MSPE-adj	p-value	R^2_{os} (%)	MSPE-adj	p-value	R^2_{os} (%)	MSPE-adj	p-value
HARL	—	—	—	—	—	—	—	—	—
HARL-PIVS	**1.018**	**17.882**	**0.000**	0.265	9.558	0.002	−0.074	2.841	0.396
HARL-NIVS	**0.539**	**10.438**	**0.000**	−0.072	0.320	0.804	0.023	2.349	0.188
HARL-TIVS	−0.045	0.814	0.418	−0.126	1.068	0.587	−0.087	3.250	0.338
HARL-EPU	0.045	3.612	0.028	−0.040	3.589	0.164	0.133	14.789	0.024
HARL-SKEW	0.040	5.604	0.008	−0.251	6.158	0.092	−1.248	−3.684	0.588
HARL-VOL	0.158	0.001	0.003	0.030	0.002	0.000	**0.742**	**0.008**	**0.000**
HARL-SEN	0.116	0.001	0.004	**0.845**	**0.004**	**0.000**	**3.117**	**0.019**	**0.000**

This table reports the out-of-sample R^2 test results based on the logarithmic transformation of Benchmark 1. The statistical significance of R^2_{os} is determined VIA the p-value from the MSFE-adjusted statistic, referred to as MSFE-adj in the table, following the method described in Ref. [23]. The out-of-sample R^2 values exceeding 0.5% and statistically significant at the 1% level are highlighted in bold.

to December 31, 2019. Table A2 presents the out-of-sample R^2 test results for these periods. The conclusions from this analysis align with our previous findings: PIVS, the IVS factor based on stock price pressure, provides more relevant information for predicting volatility.

A.3 Explanation of improved prediction accuracy using PIVS

When there are no arbitrage opportunities in the market and the underlying asset does not pay dividends, the put-call parity relationship can be expressed as follows:

$$C_t - P_t + K\mathrm{e}^{r(T-t)} = S_t,$$

where C_t and P_t denote the market prices of the call and put options at time t, respectively; S_t is the market price of the underlying asset at time t; K is the strike price; r is the risk-free interest rate; and T is the option's maturity date.

According to Cremers and Weinbaum[5], when put-call parity holds, the implied volatilities of the call and put options should be equal ($\sigma_{\mathrm{call}} = \sigma_{\mathrm{put}}$), implying that the implied volatility spread (IVS) is zero (i.e., IVS$= \sigma_{\mathrm{call}} - \sigma_{\mathrm{put}} = 0$).

However, in real markets, put-call parity does not always hold. According to option pricing theory[5], when $S_t < C_t - P_t + K\mathrm{e}^{r(T-t)}$, the implied volatility of the call option tends to be greater than that of put, resulting in a positive implied volatility spread ($IVS_t > 0$, where IVS_t denote the implied volatility spread at time t). Conversely, when $S_t > C_t - P_t + K\mathrm{e}^{r(T-t)}$, the implied volatility of the put option may exceed that of the call, leading to a negative implied volatility spread ($IVS_t < 0$).

To explain this deviation, some studies[1,10–12] introduce the concept of the "option-implied stock value" in the options market, denoted $S_{imp,t}$, defined as:

$$C_t - P_t + K\mathrm{e}^{r(T-t)} \triangleq S_{imp,t}.$$

When $S_{imp,t} > S_t$, it suggests that the option-implied stock value exceeds the actual traded market price; the opposite holds when $S_{imp,t} < S_t$.

Goncalves-Pinto et al.[11] argue that such a discrepancy may arise from price pressures in the stock market, whereas the options market may better reflect true market expectations. As shown in Fig. A1, when $S_t > S_{imp,t}$ (i.e., $IVS_t < 0$), this may indicate upward price pressure during the interval $[t-1, t]$, as reflected by a positive price change $\Delta S_t = S_t - S_{t-1} > 0$, pushing the traded price above the option-implied value. Conversely, when $S_t < S_{imp,t}$ (i.e., $IVS_t > 0$), it may reflect a downward price pressure, as evidenced by a negative price change $\Delta S_t = S_t - S_{t-1} < 0$, causing the stock's traded price to fall below its option-implied value. The stronger the price pressure is, the greater the deviation between $S_{imp,t}$ and S_t, and thus, the larger the deviation of IVS_t from zero.

On the basis of these observations, we construct a "price-pressure implied volatility spread" (PIVS) factor to quantify this phenomenon. Specifically, we average the IVS values in cases where the direction of the price change is opposite to the sign of the IVS: that is, when $\Delta S_t > 0$ and $IVS_t < 0$, or when $\Delta S_t < 0$ and $IVS_t > 0$. Larger magnitudes of PIVS may reflect stronger upward or downward pressure on the underlying asset's price, which may lead to larger fluctuations in future stock prices and, in turn, signal higher future volatility. Therefore, the PIVS factor may contain information that is useful for predicting market volatility.

For comparison, we also construct two competing factors to evaluate the predictive performance of PIVS:

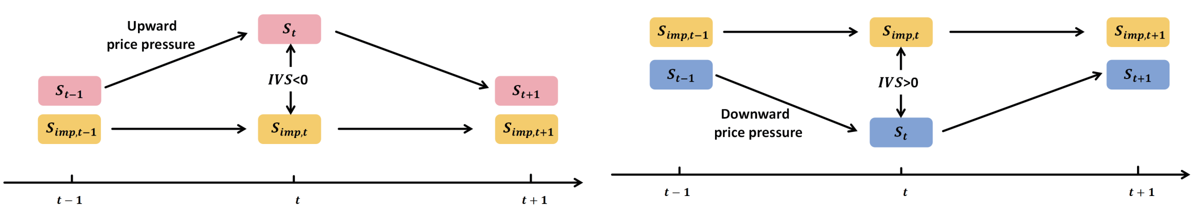
Non-price-pressure IVS (NIVS): This factor averages IVS values in cases where the sign of the IVS aligns with the direction

CSTR: 32290.14.JUSTC-2025-0031
DOI: 10.52396/JUSTC-2025-0031
JUSTC, **2025**, 55(X):

Table A2. Out-of-sample performance using different forecasting periods.

	1-day horizon			5-day horizon			22-day horizon		
	R^2_{os} (%)	MSPE-adj	p-value	R^2_{os} (%)	MSPE-adj	p-value	R^2_{os} (%)	MSPE-adj	p-value
Panel A: Subperiod 2000.01–2009.12									
HAR	—	—	—	—	—	—	—	—	—
HAR-PIVS	**1.536**	**1.022**	**0.075**	**1.190**	**1.107**	**0.097**	**0.754**	**1.152**	**0.083**
HAR-NIVS	−0.219	0.028	0.809	−0.417	−0.193	0.183	−0.289	−0.121	0.838
HAR-TIVS	−0.031	0.144	0.691	0.424	0.543	0.458	0.582	1.080	0.243
HAR-EPU	0.350	0.305	0.174	**0.865**	**0.924**	**0.056**	0.696	1.410	0.125
HAR-SKEW	0.123	0.301	0.324	0.804	0.930	0.117	**2.076**	**2.924**	**0.001**
HAR-VOL	−0.990	−0.014	0.965	−0.699	0.726	0.198	0.198	6.323	0.001
HAR-SEN	−0.404	0.066	0.834	**1.406**	**2.148**	**0.040**	**8.909**	**17.974**	**0.000**
Panel B: Subperiod 2010.01–2019.12									
HAR	—	—	—	—	—	—	—	—	—
HAR-PIVS	**2.058**	**0.515**	**0.000**	**1.151**	**0.457**	**0.001**	−0.247	−0.044	0.373
HAR-NIVS	0.288	0.103	0.071	0.022	0.012	0.581	0.188	0.092	0.088
HAR-TIVS	0.294	0.099	0.123	0.280	0.155	0.081	−0.143	−0.006	0.914
HAR-EPU	−0.133	−0.007	0.669	−0.109	0.101	0.259	0.003	0.177	0.238
HAR-SKEW	−0.214	−0.019	0.087	−0.377	−0.048	0.187	−0.996	−0.159	0.067
HAR-VOL	0.185	0.036	0.156	−0.306	−0.034	0.398	−0.150	−0.020	0.628
HAR-SEN	−0.186	0.009	0.766	−0.537	0.091	0.389	−1.063	0.143	0.400

This table shows the out-of-sample R^2 test for two alternative forecasting windows. The statistical significance of R^2_{os} is determined via the p-value from the MSFE-adjusted statistic, referred to as MSFE-adj in the table, following the method described in Ref. [23]. The out-of-sample R^2 values exceeding 0.5% and statistically significant at the 1% level are highlighted in bold.



(a) Upward Price Pressure and IVS (b) Downward Price Pressure and IVS

Fig. A1. Price pressure and IVS. This figure illustrates how discrepancies between the option-implied stock value and the actual traded stock price—whether the implied price is lower than the traded price ($IVS_t < 0$) or higher ($IVS_t > 0$)—may reflect underlying price pressure in the stock market. In this context, S_t denotes the traded stock price at time t, $S_{imp,t}$ represents the option-implied stock value at the same time, and IVS_t refers to the implied volatility spread observed at time t.

of the price change. Since NIVS may reflect implied volatility that is consistent with prevailing price trends, it might capture primarily market consensus and contain less information about price pressure, which could result in weaker predictive power for market volatility.

Total IVS (TIVS): This factor takes the average of all IVS values without conditioning on the price movement direction. As it does not distinguish between potentially informative signals and noise, its predictive ability may be diluted.

CSTR: 32290.14.JUSTC-2025-0031
DOI: 10.52396/JUSTC-2025-0031
JUSTC, **2025**, 55(X):